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Identification of Nuclear Plant Accidents Using AI

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Abstract: *If accidents happen in NPPs, operators will try to find out abnormal plant states by observing the temporal trends of some important parameters. However, operators are provided with a part of information and there is not enough time to analyze the information. In this regard, the objective of this study is to identify the accidents when the accidents happen in NPPs. We applied the support vector classification (SVC) model to identify the initiating events of critical accidents. The proposed algorithm uses the short time-integrated simulated sensor signals after the reactor trip. The results show that the SVC model can accurately identify initial events. Therefore, the identification of nuclear plant accidents is useful for NPP operators when they try to manage accidents at NPPs.*

Keywords: *Nuclear power plant, artificial intelligence (AI), support vector classification (SVC), identification*

1. Introduction

an accident occurs in a nuclear power plant, the operators might be provided with only partial information or not have sufficient time to analyze the accident in emergency. So, it is very difficult for operators to predict the progression of the accidents by staring at temporal trends of some parameters on large display panels in the main control room (MCR).

In case of the accidents that happens in a nuclear power plants (NPPs), it is very essential to identify its accidents for the operator. Therefore, in order to effectively manage the accidents, the initial short time trends of major parameters have to be observed and NPP accidents have to accurately be identified to provide its information to operators and technicians [1].

In this regard, the objective of this study is to identify the accidents when the accidents happen in a NPPs. In this study, we applied the support vector classification (SVC) model to identify the initiation events of critical accidents such as loss of coolant accidents (LOCA), total loss of feedwater (TLOFW), station blackout (SBO), steam generator tube rupture (SGTR), main steam line break (MSLB), feedwater line break (FWLB), and MSLB combined with SGTR. Input variables to the SVC are the initial integral values of the signal measured in the reactor coolant system (RCS), steam generator, and containment building after reactor trip. The proposed SVC model is verified by using the simulation data of the modular accident analysis program (MAAP4) code [2].

2. Methods

2.1. Support Vector Machine (SVM)

Support vector machine (SVM) is based on statistical learning theory that uses the obtained probability distribution in the process that targets a learning diagnosis of category information and training data to estimate the decision making function. The basic principle of the learning theory is divided into the empirical risk minimization (ERM) and a structural risk minimization (SRM). ERM minimizes learning error by using learning data. SRM selects the decision making function that minimizes the empirical risk for the subgroup after subdividing a whole group into subgroups. SVM can be applied to classification and regression problems [3].

2.2. Support Vector Classification (SVC)

A support vector classification (SVC) model is used as a classifier to classify the data of a non-linear form. It makes the decision principle to classify a data vector into a binary form such as . Optimal separating hyperplane maximizes the distance between the boundary surface and the closest data without an error. Fig. 1 shows the optimal separating hyperplane.

Fig. 2 shows an example of a binary classification by SVC model. A variety of decision boundaries exist if there is a dataset as shown in the figure. Fig. 2 shows the most stable and balanced decision boundary. There is a certain distance between the decision boundary and the actual dataset and this gap is called margin.

A boundary surface in the SVC is expressed as . The boundary surface to accurately classify the data is a boundary surface that minimizes (1) [4].

$$\begin{gathered}\Phi(\mathbf{w}) = \frac{1}{2}\mathbf{w}\,\mathbf{w} \\ y\left(\mathbf{w}\cdot\mathbf{x} + b\right) \geq 1\end{gathered} \tag{1}$$

Lagrange function should be minimized with respect to $\mathbf{w}$ and b , and should be maximized with respect to $\alpha \geq 0$. Equation (3) shows the minimum with respect to $\mathbf{w}$ and b. Equation (4) shows the maximum with respect to $\alpha \geq 0$.

$$\Phi(\mathbf{w}, b, \alpha) = \frac{1}{2}\mathbf{w}\,\mathbf{w} - \alpha\left[y\left(\mathbf{w}\cdot\mathbf{x} + b\right) - 1\right] \tag{2}$$

$$\begin{gathered}\frac{\partial \Phi}{\partial \mathbf{w}} = \mathbf{0} \quad \Rightarrow \quad \mathbf{w} = \sum_{i=1}^{N} \alpha_i y_i \mathbf{x}_i \\ \frac{\partial \Phi}{\partial b} = 0 \quad \Rightarrow \quad \sum_{i=1}^{N} \alpha_i y_i = 0\end{gathered} \tag{3}$$

$$\begin{gathered}\max_{\alpha}\left(-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j \mathbf{x}_i\cdot\mathbf{x}_j + \sum_{i=1}^{N}\alpha_i\right) \\ \min_{\alpha}\left(\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j \mathbf{x}_i\cdot\mathbf{x}_j - \sum_{i=1}^{N}\alpha_i\right)\end{gathered} \tag{4}$$

Subject to the constraints

$$\begin{cases}\alpha_i \geq 0, \ i = 1, \cdots, N \\ \displaystyle\sum_{i=1}^{N}\alpha_i y_i = 0\end{cases}$$

Minimizing with respect to $\mathbf{w}$ and b, and maximizing with respect to $\alpha \geq 0$, an optimal separating hyperplane can be expressed as (5).

$$\begin{gathered}\mathbf{w}\cdot\mathbf{x} + b = 0, \\ \mathbf{w} = \sum_{i=1}^{N}\alpha_i y_i \mathbf{x}_i, \quad b = -\frac{1}{2}\mathbf{w}^T(\mathbf{x}_r + \mathbf{x}_s)\end{gathered} \tag{5}$$

$\mathbf{w}^T\mathbf{w}$ should be minimized to maximize the distance between the two parallel dotted lines shown in Fig. 2. The generalized optimal separating hyperplane is determined by minimizing the following functional as follows:

$$\Phi(\mathbf{w},\boldsymbol{\xi}) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + \lambda\sum_{i=1}^{N}\xi_i \tag{6}$$

Subject to the constraints

$$\begin{cases} y_i\left(\mathbf{w}\cdot\mathbf{x}_i + b\right) \ge 1-\xi_i, & i=1,2,\cdots,N \\ \xi_i \ge 0, & i=1,2,\cdots,N \end{cases}$$

Where

$$\mathbf{w} = \begin{bmatrix} w_1 & w_2 & \cdots & w_m \end{bmatrix}^T$$

$$\boldsymbol{\xi} = \begin{bmatrix} \xi_1 & \xi_2 & \cdots & \xi_N \end{bmatrix}^T$$

The non-negative parameter ξ_i in the second term of (6) was used to deal with the problems associated with a misclassification due to the noise on the data. In Fig. 3, the filled triangle and rectangle indicate the data with measurement noise. The parameter ξ_i is a measure of the misclassification.

In the case where the linear boundary in the input spaces cannot separate the two classes properly, it is possible to create a hyperplane that allows a linear separation in higher dimensional feature space. The SVC models carry out this task by implicitly mapping the training data into higher dimensional feature space. A hyperplane is then constructed in this feature space that bisects the two categories and maximizes the margin of separation between itself and those points lying closest to it. Specifically, the primal space is transformed into high dimensional feature space by a nonlinear map $\boldsymbol{\varphi}(\mathbf{x})$, as shown in Fig. 4. The function, $\phi_i(\mathbf{x})$, is called the feature that is nonlinearly mapped from the input space $\mathbf{x}$, and $\boldsymbol{\varphi} = \begin{bmatrix} \phi_1 & \phi_2 & \cdots & \phi_N \end{bmatrix}^T$. Fig. 4 shows the hyperplane established in high dimensional feature space and the nonlinear classification is replaced by a linear classification problem in high dimensional feature space. The parameter, λ, in (6) controls the trade-off between the complexity of the SVC model and the number of non-separable points, and is referred to as a regularization parameter. The Lagrange multiplier technique and standard quadratic optimization technique are used to solve the vector $\mathbf{w}$ and the bias b, and the solution to the convex optimization problem can be expressed as follows [4]:

$$f(x) = \operatorname{sgn}\left(\sum_{i\in SVs}\alpha_i y_i K(\mathbf{x}_i,\mathbf{x}) + b\right) \tag{7}$$

Where

$$b^* = -\frac{1}{2}\sum_{i=1}^{N}\alpha_i y_i\left[K(\mathbf{x}_i,\mathbf{x}_r) + K(\mathbf{x}_i,\mathbf{x}_s)\right]$$

$$K(\mathbf{x}_i,\mathbf{x}) = \boldsymbol{\varphi}^T(\mathbf{x}_i)\boldsymbol{\varphi}(\mathbf{x})$$

$$K(\mathbf{x}_i,\mathbf{x}) = \exp\left(-\frac{(\mathbf{x}-\mathbf{x}_i)^T(\mathbf{x}-\mathbf{x}_i)}{2\sigma^2}\right)$$

3. Application to Identification Of NPP Accident

SVC model is used as a classifier for classifying the data of the non-linear form. The input variables of the SVC model are composed of the signal measured at RCS, steam generator, and containment building. After reactor trip, major accidents are classified by using a very short time integral value of the measured signal. That is, the input variables of the SVC model are integral values of the simulated sensor signals 13 [1].

The data was obtained using MAAP4 code. The total simulation number of accident scenarios is 820. These acquired data are divided into training data and test data. The training data consist of 190 hot-leg LOCAs, 190 cold-leg LOCAs, 190 SGTR, 2 SBO, 2 TLOFW, 5 MSLB, 5 FWLB, and 190 MSLB_SGTR. The test data consist of 10 hot-leg LOCAs, 10 cold-leg LOCAs, 10 SGTR, 1 SBO, 1 TLOFW, 2 MSLB, 2 FWLB, and 10

MSLB_SGTR.

In this study, since the SVC model is a binary classification model, four SVC models were used to classify eight types of events according to NPP accidents. The four SVC models were trained so that they categorize the hot-leg LOCA, the cold-leg LOCA, the SGTR, the SBO, the TLOFW, the MSLB, the FWLB, and the MSLB_SGTR as (1, 1, 1, 1), (1, 1, 1, -1), (1, 1, -1, 1), (1, 1, -1, -1), (1, -1, 1, 1), (1, -1, 1, -1), (1, -1, -1, 1), (1, -1,-1, -1) respectively as shown in Table I. NPP accidents are identified by the trained SVC model as shown in Fig. 5. As a result, perfect identification of events in case of no measurement errors is shown in Table II. That is, perfect identification was accomplished even though very short time measurement values were used. Since the aforementioned results were generated from simulated data, it was assumed that there were no measurement errors in the input signals [1].

Now, six types of measurement errors are assumed to check the effect of the measurement error on the proposed SVC model. Table III shows the result under the assumption of measurement errors. Despite of measurement errors, the SVC model identifies NPP accidents accurately more than 99.2%. Table IV shows results when the safety system operated. In this case, SVC model identifies accidents accurately.

TABLE I: Accident Identification using the SVC Model Or Magnetic Properties

SVC	Hot-leg LOCA	Cold-leg LOCA	SGTR	SBO	TLOFW	MSLB	FWLB	MSLB_SGTR	"Don't know" classification
SVC1	1	1	1	1	1	1	1	1	otherwise
SVC2	1	1	1	1	-1	-1	-1	-1	
SVC3	1	1	-1	-1	1	1	-1	-1	
SVC4	1	-1	1	-1	1	-1	1	-1	

TABLE II: Transient Identification (without measurement errors)

Integrating Time	Misclassification No	Don't Know classification No.
3	1	0
5	0	0
10	0	0

TABLE III: Transient Identification (with measurement errors)

Performance result	Integrating time (sec)	Total data = 820					
		-3% bias error	3% bias error	-5% bias error	5% bias error	Random (below3%)	Random (below5%)
No. of Misclassification	3	0	1	1	1	1	1
	5	1	1	1	1	0	1
	10	2	4	3	6	0	0

TABLE IV: Transient Identification (safety system actuation)

Performance result	Total data = 820	
	Integrating time (sec)	No. of Misclassification
SVC	3	1
	5	0
	10	0

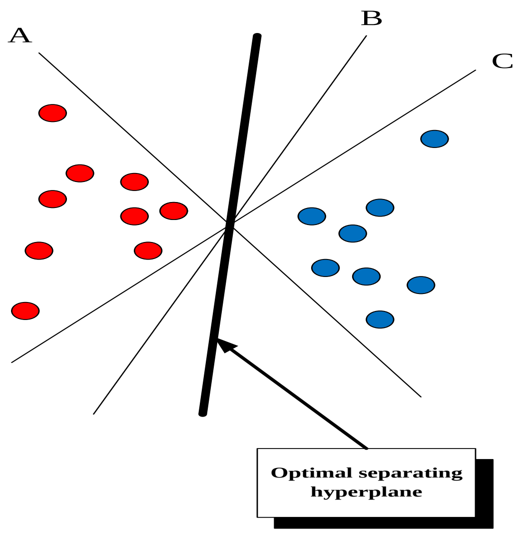

Fig. 1: Optimal separating hyperplane

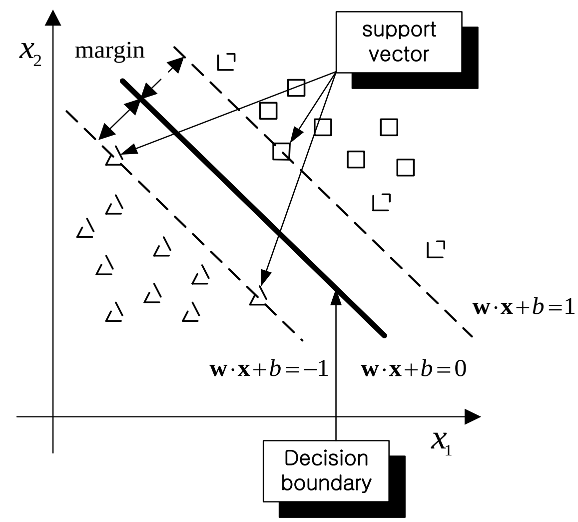

Fig. 2: An example of a binary classification using svc model

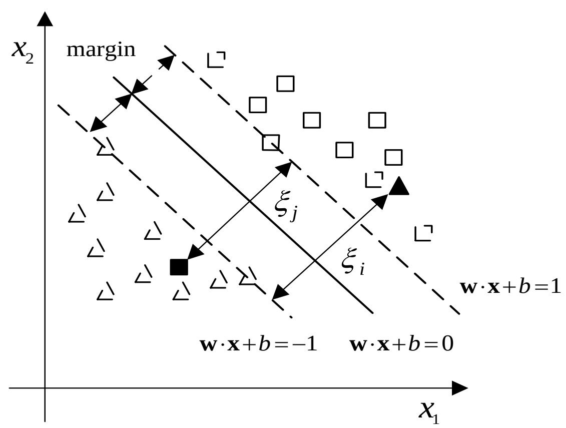

Fig. 3: An example of a misclassification due to noise in the measured data

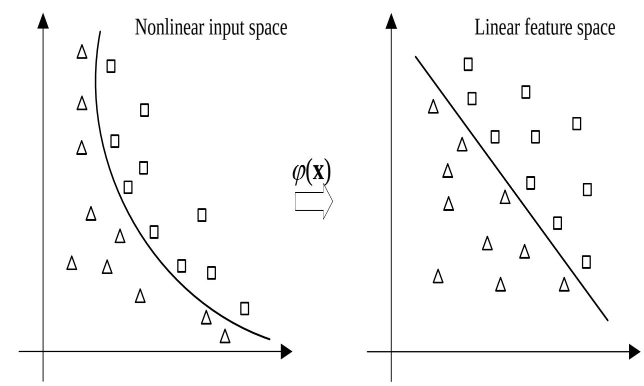

Fig. 4: Mapping to linear feature space from nonlinear input space

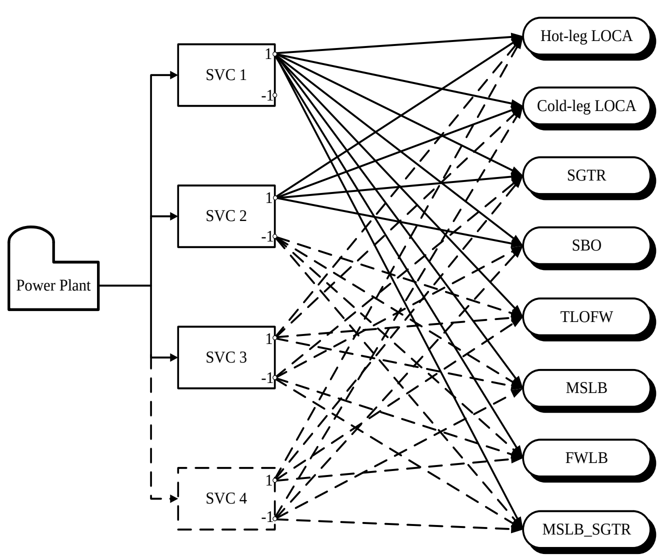

Fig. 5: Accidents identification using the svc model

4. Conclusions

In this study, the proposed SVC model is verified by using the simulation data of MAAP4 code. We used an initial integral values of the simulated sensor signals to identify the NPP accidents. The training data was used to train the SVC model. And, the trained model was confirmed using the test data. As a result, it was known that it can accurately classify eight events. Since the proposed model uses initial data after reactor trip and the initial simulation data was known to be accurate, it can be effectively used in an actual NPPs as well. By providing accurate information for accidents in a NPP, it will be helpful for the operators to rapidly respond to the accident situations.

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6. References

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